Influential factors and spatiotemporal patterns of environmental sound levels

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Environmental sound levels often represent the cumulative contributions of many types - and possibly an uncountable number - of sound sources necessitating a statistical approach to modeling. Machine learning algorithms have been used to build regression models that predict sound levels across the contiguous United States. These models discern often nonlinear and interacting relationships between measured sound levels and local environmental summaries extracted from nationwide geospatial data layers. Tens of environmental factors were examined including climate, topography, human activity, and time of day. Diagnostic tools, like partial dependence plots, can reveal the effects of influential factors on measured sound spectra. These results illustrate the foundations of many spatiotemporal patterns in acoustic resource conditions, and provide tools for understanding the potential consequences of shifts in environmental conditions. Modeled predictions of ambient one-third octave band sound levels also provide a tool for predicting the audibility of noise on large landscape scales.

1 INTRODUCTION

Environmental sound levels are summaries of all ambient acoustical energy at a particular place and time outdoors. Prominent sources include transportation, industry, recreational activities, weather, and flowing water. Environmental noise is extraneous or unwanted sound, and urban noise problems have a long history and global significance. As in many other urban centers, noise is the number one complaint to the New York City Department of Environmental Protection[1]. In addition, noise is not confined to urban areas, and the effects of noise are not

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confined to humans. Recent work has documented substantial changes in animal foraging and anti-predator behavior, reproductive success, population density, and community structure due to anthropogenic noise[2].

The ecological breadth of noise impacts is presaged by the ubiquity and extent of anatomical investment in the auditory sense among most multicellular organisms. Hearing provides panoramic environmental awareness, alerting animals to events near and far, past and present. Sounds provide information about a diverse range of physiographical, biological, and anthropogenic processes and events. Environmental sounds exhibit consistent patterns across time and space: windy afternoons, dawn choruses of birds, nocturnal choruses of frogs and insects, and rush hours of human transportation.

Given the adverse effects of noise, it is critical to understand its spatial extent and the factors that most strongly affect various measures of noise exposure. Many noise studies account for a single source in a limited area, to realize a tractable scenario for noise propagation modeling. Many noise studies focus on a single noise metric. Single metrics and thresholds may fail to capture important information. For example, the majority of aircraft noise complaints received in Australia come from people who live outside the published noise contours[3].

The diversity of contributions to environmental sound levels combines with the impracticality of comprehensive measurement to suggests a statistical approach to modeling. Statistical models can extract patterns from a large number of point measurements to predict patterns that apply over large spatial scales. In this paper we take a few steps towards exploring the spatiotemporal patterns of environmental sound that exist on landscape scales. Our focus is on available data and a geospatial sound modeling framework. Geospatial sound modeling was introduced in the context one-third octave band sound pressure level (SPL) spectra measured in National Park Service (NPS) units, most of which were distant from urban areas[4]. Here, we extend the analysis of environmental sound across the contiguous United States to include urban as well as rural areas.

2 EMPIRICAL DATA

2.1 Environmental Sound Levels

The United States has an enormous range of acoustic diversity, from painfully loud conditions at the edge of airport runways to dormant volcanic craters so quiet that the best sound level meters are inadequate to measure their sound levels. Dry, barren habitats may be devoid of any local sound sources for long periods of time, whereas lush wetlands may contain uncountable numbers of sound sources most of the time. Two data sets, natural and urban, were used to address the acoustic diversity of the country. In total, roughly 1.5 million hours from 492 geographically unique site locations distributed across the contiguous United States were incorporated; a map of the site locations appears in Figure 1.

The natural dataset came from the archive of NPS acoustical measurements collected in National Park units during the years from 2000 to 2014. Note that the term natural is used instead of rural, recognizing the superlative environmental quality that is the management standard for these units. The urban data includes a small subset of sites that are classified as rural by the United States Census Bureau[5]. Seasonal exceedance level metrics were derived from one second A-weighted L_{eq} measurements made using ANSI Type 1 sound level meters. The durations of measurements in natural areas are typically 25 days or longer to obtain statistics encompassing a representative sample of weather and other varying factors. 498 seasonal observations from 333 unique locations were calculated. Further details regarding the measurements and subsequent processing have been published elsewhere[4].

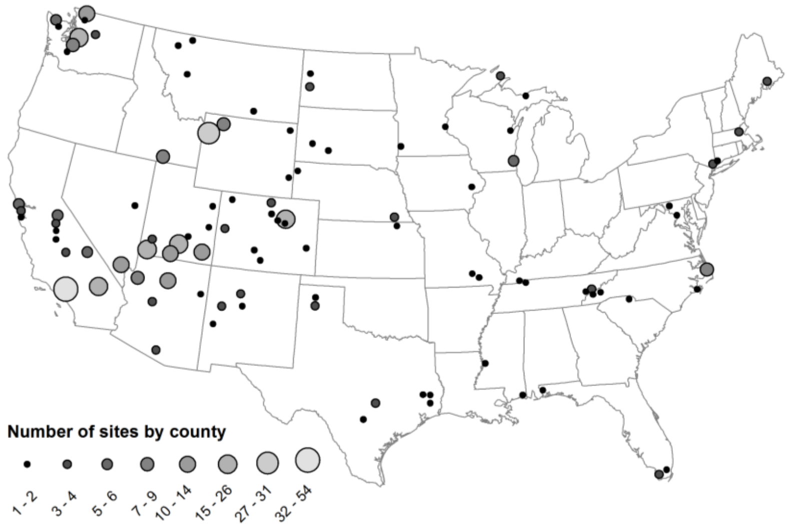

Fig. 1 – Map of natural and urban site locations.

The urban data set is a collection of measurements from airport noise monitoring systems[6] and NPS sites in 14 urbanized areas[5] across the United States: San Antonio, TX, Austin, TX, Vicksburg, MS, Los Angeles, CA, Riverside, CA, Kill Devil Hills, NC, San Francisco, CA, Washington, DC, Denver, CO, Bridgeport, CT, New York, NY, Boston, MA, Milwaukee, WI, and Seattle, WA. Many airports maintain several noise monitoring systems in the airport vicinity and surrounding community (the set considered contains site locations up to 25 km from the airport). Protocols and equipment vary, but all airports reported several A-weighted statistics for each hour of the day during the year 2013. These hourly data were summarized using methods similar to the natural set to generate comparable metrics for 497 seasonal observations from 159 unique urban locations.

Seasonal hourly A-weighted L_{50} SPL for the 995 observations were calculated from available measurements; box and whisker plots of these observations are shown in Figure 2. The natural levels range from 8 dBA to 69 dBA, although the lowest measurements are biased upwards by the self-noise of the equipment. The median of natural levels follows the shape of a typical temperature profile during the day, gradually increasing after sunrise and falling after sunset. The dynamic range of urban levels is narrower than natural. The urban levels began rising sharply at 5AM to a maximum at 8AM, then remain fairly constant until the evening rush hour which peaks at 6PM.

2.2 Physiographical data

The spatial patterns of sound levels are dependent on a complex linkage of environmental and anthropogenic factors. To formulate a model we considered many factors that might influence acoustic propagation, the presence of acoustic sources, or both. For the most part, our choice of variables was limited to what could be derived from available geospatial data layers with national coverage. It also included variables that describe the time of measurement and control for the varying equipment used.

In total, 115 potential explanatory variables in 7 categories were considered: topography, climate, landcover, hydrology, anthropogenic, time, and control. Many of the variables are variations of a given quantity that has been summarized using multiple statistics over multiple spatial scales. A list and description of the variables can be found in Table A.1; more detail on the original data layers and derivation of metrics is available[7].

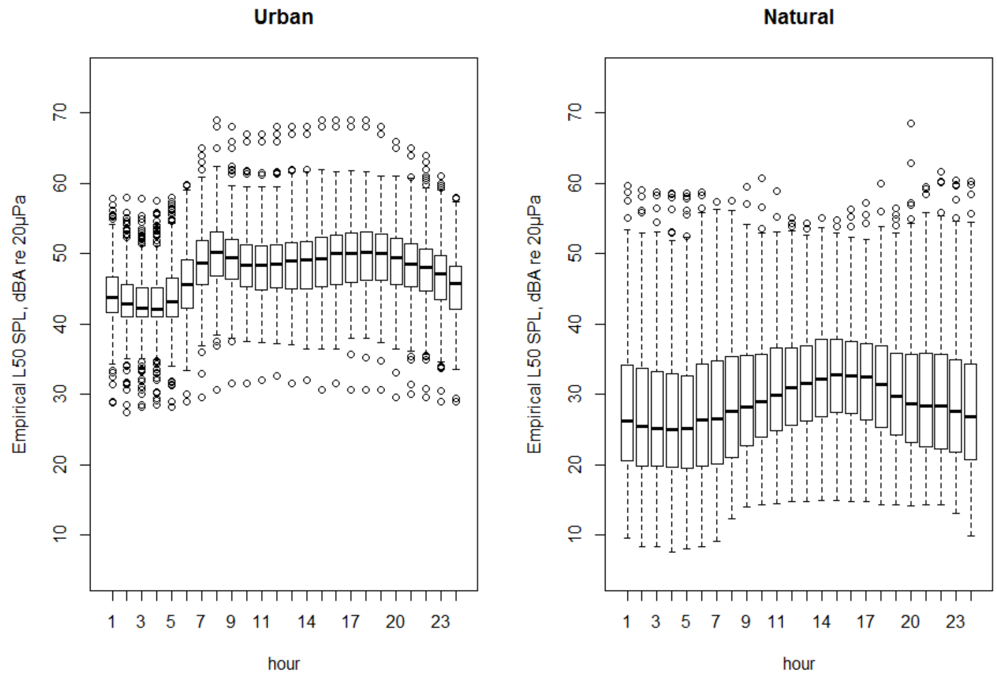

Fig. 2 – Box and whisker plots showing the quartiles, median, and outliers of the hourly A-weighted L_{50} sound pressure levels in the urban set (left panel) and natural set (right panel).

3 GEOSPATIAL MODEL OF ENVIRONMENTAL SOUND LEVELS

Geospatial sound models incorporate spatial representations of physiographical and anthropogenic factors to assess expected contributions to the existing SPL from both anthropogenic and natural sources. The models do not directly apply the physics of sound propagation or characteristics of individual sound sources. Instead, a regression model is trained to find relationships between the explanatory variables and response[4]. Models are based on the Random Forest algorithm[8]; this is an ensemble method that can capture spatiotemporal patterns that may be exhibited by only a small portion of the available sample.

3.1 Influential explanatory variables

Identifying the influential explanatory variables is crucial to model formulation and a first step towards understanding spatiotemporal patterns of sound levels. For this work, variable rankings are based on how much error is induced by permutations of that quantity, which can also influence interactions. It is also important to keep in mind that sound levels are dominated by the loudest signals.

The dominant factors driving the A-weighted L_{50} SPL are related to land use, climate, and traffic corridors. The variables in the optimal model are listed below in Table 1, ranked by importance. The other potential explanatory variables decrease the predictive power of the model and were omitted. It is likely that these factors are irrelevant. However it is also possible that a given quantity was poorly represented or its influence was not significant within the available training data.

Table 1 – Variables included in the daytime A-weighted L_{50} geospatial sound model.

Rank	Name	Rank	Name	Rank	Name
1	VIIRS_270_Mean	16	DistRoadsAll	31	PopTotal50km
2	Shrubland5km	17	TAvgNorms	32	Slope
3	PhysicalAccess	18	Elevation	33	FlightFreq
4	TAvgWint	19	VIIRS_69120_Mean	34	DistCoast
5	PPTNorms	20	Developed5km	35	DistAirpHigh
6	VIIRS_4320_Min	21	TDewAvgWint	36	UrbanLow200m
7	TDewNorms	22	VIIRS_4320_Mean	37	DistStreamO4
8	Forest5km	23	DistRoadsMajor	38	Extractive5km
9	PPTSummer	24	DistAirpMoto	39	RddAllPt
10	VIIRS_1080_Min	25	Built200m	40	MilitarySum
11	VIIRS_69120_Max	26	Forest200m	41	circDayY
12	Evergreen5km	27	Grazing5km	42	circDayX
13	TDewAvgSumm	28	Wind	43	ndBA
14	DistAirpSea	29	DistAirpMod	44	DistStreamO1
15	PPTWinter	30	PopDensity50km	45	DistRailroads

3.2 Predictive performance

Geospatial models for a variety of acoustic metrics have been derived using established methods[4]. For brevity, results and discussion herein focus on the existing seasonal daytime A-weighted L_{50} SPL (the response). After identifying significant explanatory variables, the model fit was evaluated using an exhaustive leave-one-out cross validation to account for correlation among the observations. The predicted levels from a model using all observations and the predicted level from 995 cross-validated models each using a limited training set appear in Figure 3.

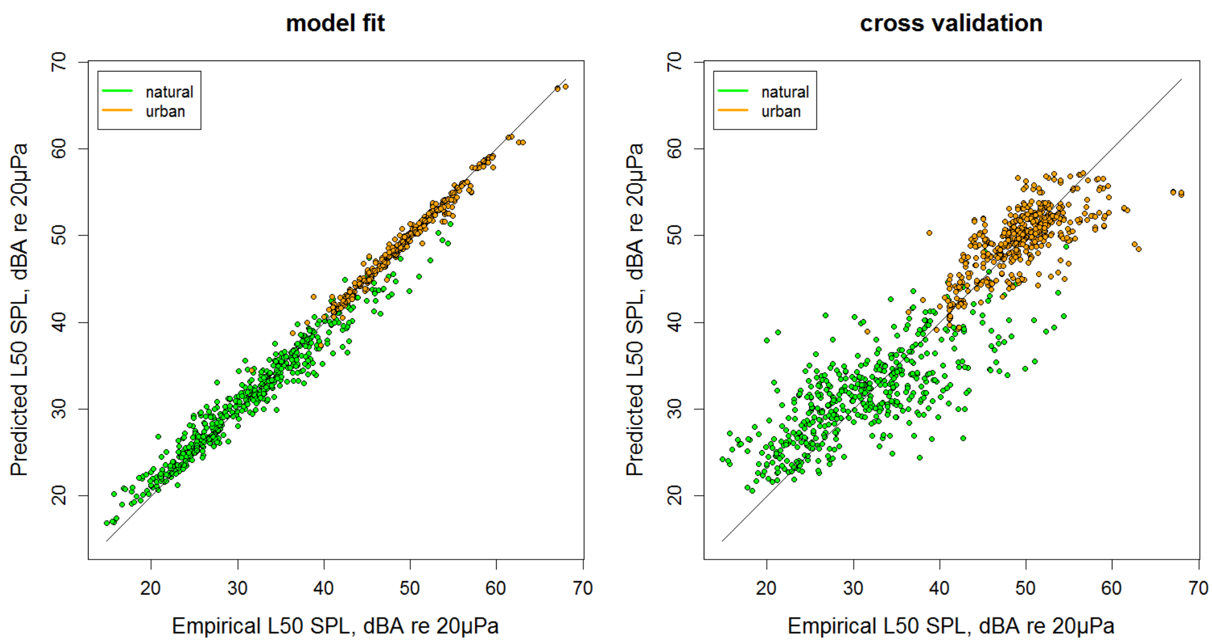

Fig. 3 – The predicted levels from a model using all observations (left panel) and cross-validated models each using a limited training set (right panel) relative to the measured SPL.

The full model fit shows excellent correlation with the empirical data ($R^2 = 0.98$). The ensemble nature of the random forest algorithm helps reduce overfitting, but any model is at risk of overfitting the training data and distorting the perceived performance. Cross validation can provide a quantitative measure of how well the model will generalize to uncharted locations outside of the available training data. In this case, collocated observations were removed from training sets to avoid bias from temporal correlation[4]. The accuracy of prediction diminishes with the knowledge of underlying patterns and thus, rare conditions are prone to error: one systematic problem is that sound levels at the quietest sites are overestimated and levels at the loudest sites are underestimated. Statistics describing the prediction accuracy relative to a null model (mean of response) are shown in Table 1.

Table 2 – Performance statistics: RMSE is the root mean squared error, MAD is the median absolute deviation, Null is the residuals of the mean, and GSM is the cross validation residuals of the geospatial sound model.

GSM, RMSE	Null, RMSE	GSM, MAD	Null, MAD	% Explained
4.40	11.12	2.29	8.7	84

The difference between the median absolute deviation and root mean square error may in part be attributed to outliers. The largest errors arise from inadequacies of the geospatial data to describe powerful, consistently active sources like nearby rivers and roads. For example, winter sound levels were overestimated at Sand Creek Massacre National Historic Site because the nearby creek was dry during the measurement period. Despite the large library of empirical data, extreme or unusual sonic environments are very sparsely represented. This compromises the model performance, and it amplifies the prediction error estimated from leave-one-out analyses. The model describes the expected long term conditions in most places.

4 DISCUSSION

4.1 Differences between urban and natural environments

The Visible Infrared Imaging Radiometer Suite (VIIRS) class of variables is very influential as indicated by Table 1. These variables describe the upward radiance at night as measured by satellite and are indicative of the degree of human habitation. More precisely, spatial analyses of light pollution in urban areas suggest that these variables commonly represent roadways and areas developed for industrial and commercial use[9]. Figure 4 shows a scatterplot of VIIRS_270_Mean and the L_{50} SPL for all observations. The VIIRS_270_Mean explanatory variable provides a clear distinction between the urban and natural sets and is likely one of the first splits in many trees of the random forest model. While VIIRS_270_Mean is uniformly close to zero for most natural observations, there is a linear relationship between the light and sound emitted in urban areas. Few other explanatory-response relationships are as direct and consistent across the sample.

Because of the structure, size and complexity of a random forest model, the relationships between response and explanatory variables are difficult to interpret relative to more common models in which a functional relationship is explicit. A partial dependence function is the average predicted response given permutations of explanatory variables and can provide some insight[4].

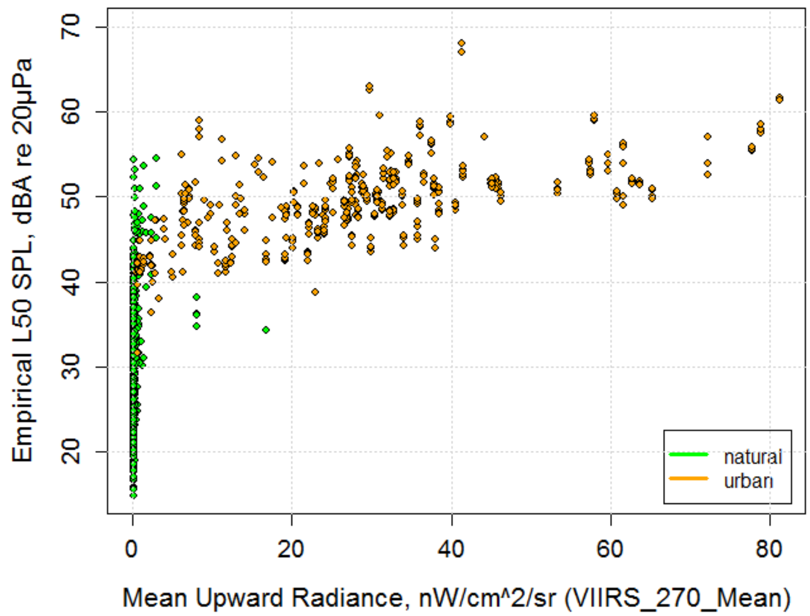

Fig. 4 – Scatterplot of VIIRS_270_Mean and emprical observations of daytime sound level.

The partial dependence of the response on the proportion of forested land cover within 5 km of the receiver location is shown in Figure 5. The left panel and right panels document the contrasting trends in urban and natural area. In natural areas, increasing amounts of forested area often lead to increased sound levels. Prominent sources are wind interacting with vegetation, and more extensive and persistent biological choruses. Note that our data set disproportionately represents drier habitats in the western U. S., and this relationship might look different in a large data set taken from wetter habitats in the eastern U. S. In urban areas, increasing amounts of forested area are often correlated with reduced industrial and transportation activity.

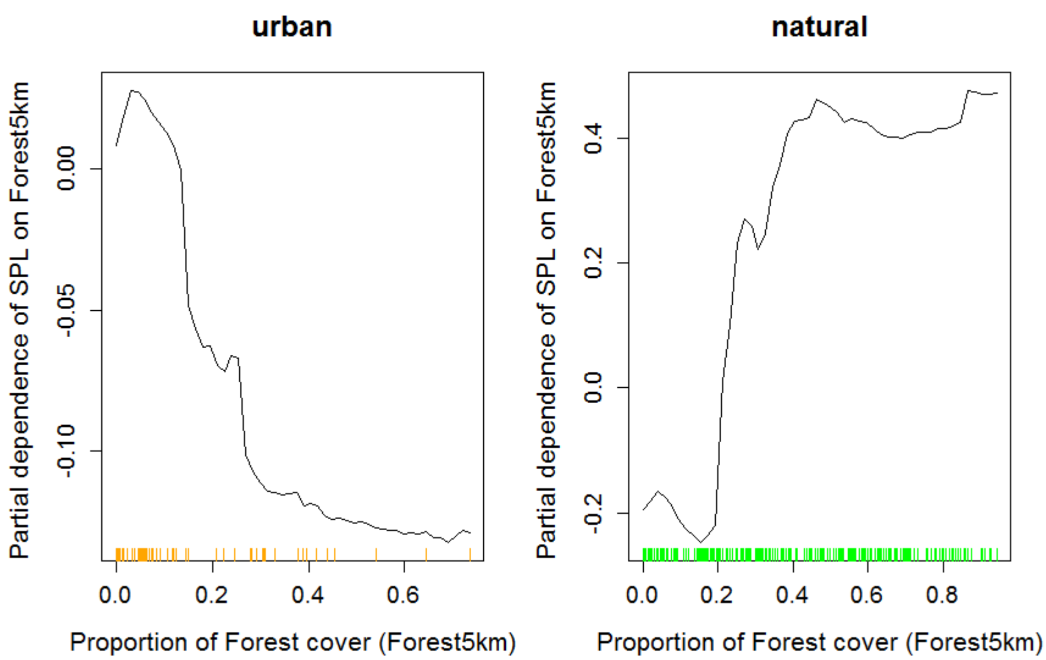

Fig. 5 – Partial dependence of the L_{50} SPL on Forest5km considering urban sites only (left) and natural sites only (right). The rug shows values of Forest5km for the observations considered.

4.1 Interacting drivers of biomes and natural sound levels

Biomes are geographic areas with similar environmental characteristics and are occupied by a set of organisms adapted for the conditions therein. Classification schemes are commonly defined by climatic parameters such as temperature and precipitation, although soil and sun exposure are also important factors[10]. Some of these factors are not explicitly included in our current geospatial sound model. Temperature, precipitation, latitude, elevation, and humidity are related, yet exceptions to these general relationships distinguish some places. For example, Figure 6 shows that the relationship between average yearly temperature and humidity is modulated by precipitation. When the simultaneous influence of two variables on a third is not purely additive, those two variables are said to interact. The presence of interactions makes formulating and interpreting models more difficult.

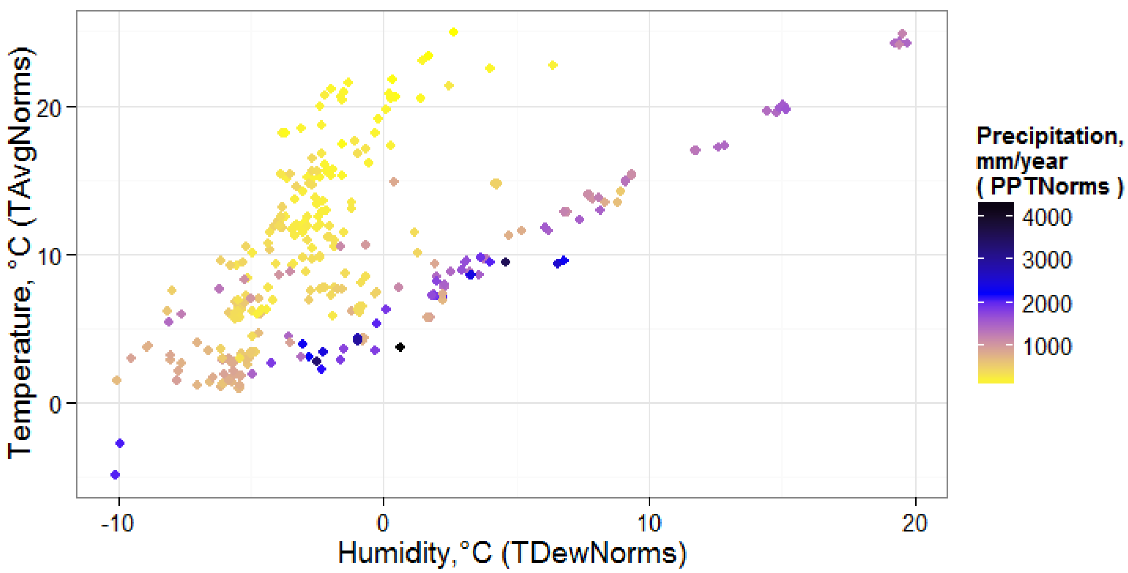

Fig. 6 – Interaction between average annual temperature, humidity, and precipitation considering the natural set only.

In terrestrial environments, biodiversity generally increases with primary production, moisture availability and temperature. Similarly, moisture and temperature are important drivers of natural sound levels. Considering the natural set only, the clearest relationship with sound pressure level is provided by moisture as described by the dew point temperature. This relationship and the interaction with elevation are shown in Figure 7. At low and mid elevations, sound levels increase with moisture. However, at very dry sites, there is an increase in level which is accompanied by high elevations (note that there is not a strong correlation between sound level and elevation alone). These sites also have lower temperatures, which actually tends to decrease sound levels. To some degree, these patterns are captured in the geospatial sound model by the random forest algorithm.

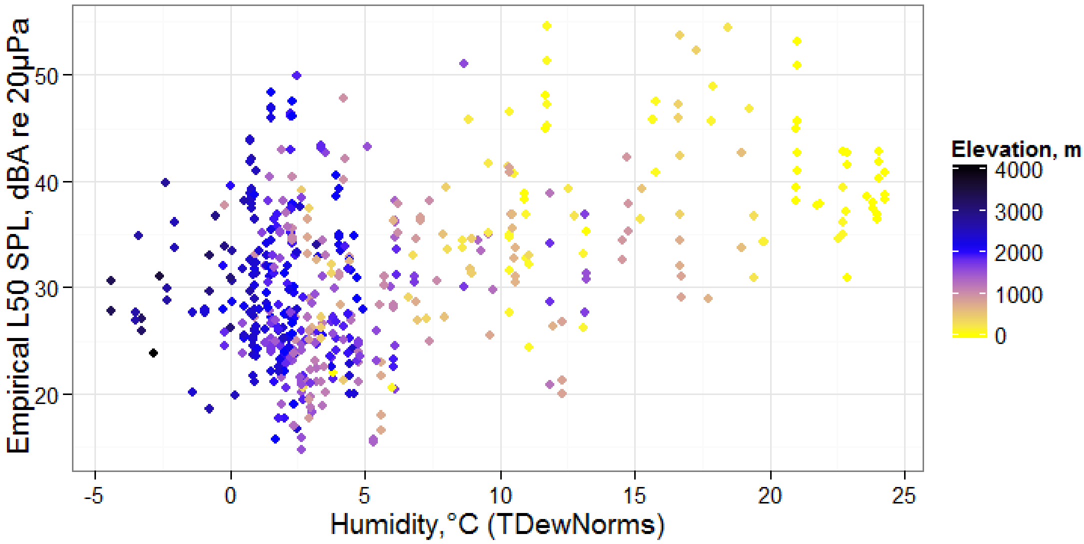

Fig. 6 – Interaction between the L_{50} sound pressure level, average annual humidity, and elevation considering the natural set only.

5 CONCLUSIONS

Environmental sound levels often integrate an uncountable number of contributing acoustic sources. The time-averaged magnitude of sound pressure is one of the most fundamental quantities we have to describe this integration. Although many important characteristics are unmeasured by this simple metric, sound levels can efficiently distinguish a wide range of acoustical conditions. In this paper, we sought a deeper understanding of how anthropogenic and physiographical factors are driving sound pressure levels across the United States.

An understanding of patterns is crucial for building models, for interpreting measured conditions, and for predicting conditions under hypothetical scenarios. The patterns described in this study were extracted from components of a geospatial sound model that was trained on empirical data from a wide range of locations and acoustical conditions. This paper helps bridge the gaps between maps of sound level, the underlying models, and explanatory geospatial data. This paper also provides a reference for improved geospatial sound models that include additional explanatory geospatial data and extended support for urban areas across the contiguous United States.

In addition to the patterns revealed by the internal structure of the geospatial model, patterns are also evident in the maps generated from the geospatial model[4, 11]. Different patterns emerge from examining these maps across a range of scales: small towns, urban areas, national parks, and larger regions. These maps provide spatially explicit pictures of ambient sound levels that will prove valuable in many contexts, including: improving predictions of noise audibility[12], guiding noise mitigation investments, providing support for large landscape conservation assessments, informing plans to enhance ecosystem resilience to climate change.

6 ACKNOWLEDGEMENTS

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A APPENDIX

Table A.1. Initial potential explanatory variables, spatial resolution, and description by category. Area of analysis indicates radius of circular area or cylindrical volume centered at site.

Variable	*Area of analysis*	*Description*	*Units*
Topography			
Elevation	Point	Digital elevation, height above sea level	meters
Slope	Point	Rate of change of elevation	degrees
TPI	Point	Topographic position index (e.g. ridge, slope, valley)	categorical
Climate			
PPTSummer	Point	10 year average summer precipitation	mm
PPTWinter	Point	10 year average winter precipitation	mm
PPTNorms	Point	10 year average yearly precipitation	mm
TAvgSumm	Point	10 year average summer average temperature	degrees C
TAvgWinter	Point	10 year average winter average temperature	degrees C
TAvgNorms	Point	10 year average yearly average temperature	degrees C
TdewAvgSumm	Point	10 year average summer minimum dew point	degrees C
TdewAvgWint	Point	10 year average winter maximum dew point	degrees C
TdewAvgNorm	Point	10 year average yearly minimum dew point	degrees C
Wind	Point	Annual mean wind speed, 1960-1990	m/s
Landcover			
Barren	200m, 5km	Proportion of Barren landcover	%
Cultivated	200m, 5km	Proportion of Cultivated landcover	%
Deciduous	200m, 5km	Proportion of Deciduous Forest landcover (level 2)	%
Developed	200m, 5km	Proportion of Developed landcover	%
Evergreen	200m, 5km	Proportion of Evergreen Forest landcover (level 2)	%
Forest	200m, 5km	Proportion of Forest landcover	%
Herbaceous	200m, 5km	Proportion of Herbaceous landcover	%
MixedForest	200m, 5km	Proportion of Mixed Forest landcover (level 2)	%
Shrub	200m, 5km	Proportion of Shrubland landcover	%
Snow	200m, 5km	Proportion of Snow landcover	%
Wetland	200m, 5km	Proportion of Wetlands landcover	%
Water	200m, 5km	Proportion of Water (only) landcover	%
Hydrology			
DistCoast	Point	Distance to nearest coastline	m
DistWaterBody	Point	Distance to nearest body of water	m
DistStreamO	Point	Distance to nearest stream with Strahler order greater than 1,3, or 4	m
Anthropgenic			
Built	200m, 5km	Degree of human modification from built land use	ratio
Commercial	200m, 5km	Degree of human modification from commercial land use	ratio
DistAirpHeli	Point	Distance to nearest heliport	m

DistAirpHigh	Point	Distance to nearest high volume airport	m
DistAirpLow	Point	Distance to nearest low volume airport	m
DistAirpMod	Point	Distance to nearest moderate volume airport	m
DistAirpMoto	Point	Distance to nearest motorized airport	m
DistAirpSea	Point	Distance to nearest seaplane airport	m
DistMilitary	Point	Distance to nearest military flight path	m
DistRailroads	Point	Distance to nearest rail line	m
DistRoadsAll	Point	Distance to nearest road (all roads)	m
DistRoadsMaj	Point	Distance to nearest road (major roads)	m
Extractive	200m, 5km	Degree of human modification from extractive land use	ratio
ExurbanHigh	200m, 5km	Degree of human modification from high exurban land use	ratio
ExurbanLow	200m, 5km	Degree of human modification from low exurban land use	ratio
FlightFreq	25km	Total weekly flight observations	count
Grazing	200m, 5km	Degree of human modification from grazing land use	ratio
Industrial	200m, 5km	Degree of human modification from industrial land use	ratio
Institutional	200m, 5km	Degree of human modification from institutional land use	ratio
MilitarySum	40 km	Sum of designated military flight paths	count
Park	200m, 5km	Degree of human modification from park land use	ratio
PhysicalAccess	point	Travel time given transportation infrastructure and off-trail permeability	ratio
PopDensity	50km	Density of individuals per 2010 US Census	count/km^2
PopTotal	point, 50km	Total number of individuals per 2010 US Census	count
RddAll	200m, 5km	Road density, sum of road lengths (all roads) divided by area of interest	km/km^2
RddMajor	200m, 5km	Road density, sum of road lengths (major roads only) divided by area of interest	km/km^2
RddWeighted	200m, 5km	Road density, sum of road lengths (weighted by class) divided by area of interest	km/km^2
Suburban	200m, 5km	Degree of human modification from suburban land use	Ratio
Timber	200m, 5km	Degree of human modification from timber land use	Ratio
Transportation	200m, 5km	Degree of human modification from transportation land use	Ratio
UrbanHigh	200m, 5km	Degree of human modification from high urban land use	Ratio
UrbanLow	200m, 5km	Degree of human modification from low urban land use	Ratio
VIIRS	270m, 1080m, 4320m, 17280m, 69120m	Maximum, Mean, and minimum upward radiance at night	nW/cm^2/sr
WaterHum	200m, 5km	Degree of human modification from water land use	Ratio
Wilderness	16 km	Sum of designated wilderness in area of interest	m^2
Time			
circDayX	Point	Annual position, spring/fall	Radians
circDayY	Point	Annual position, winter/summer	Radians
dayLength	Point	Average length of day during deployment	Hours
Control			
nf	Point	Noise floor of measurement equipment	dB SPL